A NOVEL APPROACH TO DATA MINING USING SIMPLIFIED SWARM OPTIMIZATION

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Noorhaniza Wahid

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ABSTRACT

Data mining has become an increasingly important approach to deal with the rapid growth of data collected and stored in databases. In data mining, data classification and feature selection are considered the two main factors that drive people when making decisions. However, existing traditional data classification and feature selection techniques used in data management are no longer enough for such massive data. This deficiency has prompted the need for a new intelligent data mining technique based on stochastic population-based optimization that could discover useful information from data.

In this thesis, a novel Simplified Swarm Optimization (SSO) algorithm is proposed as a rule-based classifier and for feature selection. SSO is a simplified Particle Swarm Optimization (PSO) that has a self-organising ability to emerge in highly distributed control problem space, and is flexible, robust and cost effective to solve complex computing environments. The proposed SSO classifier has been implemented to classify audio data. To the author's knowledge, this is the first time that SSO and PSO have been applied for audio classification.

Furthermore, two local search strategies, named Exchange Local Search (ELS) and Weighted Local Search (WLS), have been proposed to improve SSO performance. SSO-ELS has been implemented to classify the 13 benchmark datasets obtained from the UCI repository database. Meanwhile, SSO-WLS has been implemented in Anomaly-based Network Intrusion Detection System (A-NIDS). In A-NIDS, a novel hybrid SSO-based Rough Set (SSORS) for feature selection has also been proposed. The empirical analysis showed promising results with high classification accuracy rate achieved by all proposed techniques over audio data, UCI data and KDDCup 99 datasets. Therefore, the proposed SSO rule-based classifier with local search strategies has offered a new paradigm shift in solving complex problems in data mining which may not be able to be solved by other benchmark classifiers.

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PUBLICATIONS

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2. Wei-Chang Yeh, Noorhaniza Wahid, Yuk Ying Chung. "A Hybrid Network Intrusion Detection System using Simplified Swarm Optimization (SSO)", submitted to Applied Soft Computing (SCI journal with Impact Factor 2.415).
3. Wei-Chang Yeh, Noorhaniza Wahid, Yuk Ying Chung. "A New Simplified Swarm Optimization (SSO) Data Mining Classification Algorithm", submitted to Computers & Industrial Engineering (SCI journal with Impact Factor 1.057).

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ABBREVIATIONS

Acronym	Expended term
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ADEL	Ankyloglossia with Deviation of the Epiglottis and Larynx
AI	Artificial Intelligence
AIS	Artificial Immune Systems
A-NIDS	Anomaly-based Network Intrusion Detection Systems
ANN	Artificial Neural Network
ARS	Average Rule Size
BPSO	Binary Particle Swarm Optimization
BW	Baum-Welch
CHD	Coronary Heart Disease
CLPSO	Comprehensive Learning PSO
CPSO	Constricted PSO
CPSO	Cooperative Particle Swarm Optimizer
DE	Differential Evolution
DFT	Discrete Fourier Transform
DoS	Denial of Service
DPSO	Discrete PSO
EAs	Evolutionary Algorithms
ELS	Exchange Local Search
EP	Evolutionary Programming
ES	Evolution Strategy
FCM	Fuzzy C-Means
FCPS-classifier	Fuzzy Controlled Particle Swarm-classifier
FDTs	Fuzzy Decision Trees
FIPS	Fully Informed Particle Swarm
FN	False Negatives
FP	False Positives
FPPSO	Feature Partitioning PSO
GA	Genetic Algorithm
GEPSVM	Generalized Eigenvalue Proximal SVM
GMM	Gaussian Mixture Model
GNB	General Naive Bayes
GP	Genetic Programming
GRBF	Gaussian RBF
HEHRS	Hierarchical Rule Sets
H-IDS	Host-based IDS

Acronym	Expended term
HMM	Hidden Markov Model
IA	Immune Algorithm
IDS	Intelligent Dynamic Swarm
IDSRS	Intelligent Dynamic Swarm with Rough Set
IkNN	Informative k Nearest Neighbor
IPS-classifier	Intelligent Particle Swarm-classifier
IS	Immune System
KDD	Knowledge Data Discovery
kNN	kNearest Neighbour
KPCM	Kernel-based Possibilistic C-Means
LCM	Linear time Closed itemset Miner
LDPSO	Linearly Decreasing PSO
LDWPSO	Linear Decreasing Weight PSO
LGP	Linear Genetic Programming
LMNN	Large Margin Nearest Neighbor
LPC	Linear Predictive Coding
MARS	Multivariate Adaptive Regression Splines
MFCC	Mel Frequency Cepstral Coefficient
MI	Mutual Information
MLP	MultiLayer Perceptron
MOPSO	Multi-Objective PSO
MSSE	Mean Sum Squared Error
NB	Naive Bayes
NFL	Nearest Feature Line
NIDS	Network Intrusion Detection Systems
NIP	Numerical Interval Pruning
NN	Neural Network
NN	Nearest Neighbor
OBSI	Octave Band Signal Intensities
P2PkNN	Peer-to-Peer kNN
PCA	Principal Component Analysis
PM	Partition Matrix
PSO	Particle Swarm Optimization
PSO-NCC	PSO-Nearest Centroid Classifier
PUNN	Product Unit Neural Network
QDE	Quantum-Inspired Differential Evolution
QPPs	Quadratic Programming Problems
R2L	Remote to Local
RBF	Radial Basis Function
RHMM	Reverse HMM
RJMCMC	Reversible Jump Markov Chain Monte Carlo

Acronym	Expended term
RSC	Rough Set Classification
RSC-PGA	Rough Set Classification Parallel Genetic Algorithm
RST	Rough Sets Theory
RWS	Roulette Wheel Selection
SA	Simulated Annealing
SI	Swarm Intelligence
SMO	Sequential Minimal Optimization
SNNB	Selective Neighborhood Naive Bayes
SOM	Self Organizing Maps
SR	Silence Ratio
SSO	Simplified Swarm Optimization
SSO-ELS	SSO with Exchange Local Search
SSO-WLS	SSO with Weighted Local Search
SVDF	Support Vector Decision Function
SVM	Support Vector Machine
TN	True Negatives
TP	True Positives
TSP	Traveling Salesman Problem
TSVM	Twin SVM
U2R	User to Root
WEKA	Waikato Environment for Knowledge Analysis
WFPPSO	Weighted Feature Partitioning PSO
WLS	Weighted Local Search
WSVM	Weighted Support Vector Machine

LIST OF FIGURES

LIST OF TABLES

TABLE OF CONTENTS

CHAPTER 1. Background Information and Problem Statements

In the emerging age of digital information we are overwhelmed with data, while our capability to analyse and interpret such huge datasets lags behind. Furthermore, it has been estimated that every 20 months the amounts of data stored in the world's databases are doubled, which caused difficulties when trying to justify this figure in a quantitative sense [1]. Often, traditional data analysis, and interpretation of changing data, has become insufficient for data processing as the data volumes grow exponentially. In addition, due to the advancement of software capabilities and hardware tools that enable the automated data collection, as well as the decreasing trend in their cost, there has been a dramatic increase in the data being collected and stored in databases. Although in recent years information collection and storage has become easier and more inexpensive, great effort is required to extract relevant knowledge information from such large-scale databases. Therefore, a new generation of computational techniques and tools is required to support the extraction of useful knowledge from the rapidly growing volume of data. Hence, data mining becomes the reliable solution for elucidating the patterns that underlie it.

Data mining is the application of specific algorithms that has been widely used for extracting patterns or models from data. Two main aspects in data mining are data classification and feature selection. Data classification classifies a data item into one of several predefined categorical classes. Feature selection can be defined as a process of choosing a small subset of features from the original set of features which is necessary and sufficient to describe the target concept. Other than the well-known classical data mining techniques, heuristic approaches based on swarm intelligence algorithms have gained more attention and have been adopted in data classification problems in order to find a good solution. This thesis proposes and presents some new data mining approaches based on a population-based optimization algorithm for various data classification problems. The second topic being discussed in this thesis is about feature selection, which presents a new hybrid rough set reduction approach to feature selection. At this stage, this thesis is concerned with finding new approaches in both topics that contribute to the best classification accuracy; computation time is not taken into consideration. In this chapter, section 1.1 presents a brief discussion on data mining from the perspective of Knowledge Data Discovery (KDD). In section 1.2, the motivation is described and the problem statement in this thesis is identified. Next, the objective and contribution of the thesis is stated in section 1.3, followed by the organisation of the thesis in section 1.4.

1.1. Data Mining

Data mining is the process of analysing data from different perspectives and summarising it into useful information. It blends traditional data analysis methods with sophisticated algorithms for processing large volumes of data. It has been widely used and unifies research in fields such as statistics, databases, machine learning and Artificial Intelligence (AI). Regarding that, data mining has been seen as an explosion of interest from both academia and industry to improve the process of visualising and understanding the pattern of the data. Data mining is the core part of the Knowledge Discovery in Database (KDD) process, which is essential to solve a problem in a specific domain [2]. Generally, KDD is the overall process of identifying valid, novel, potentially useful and ultimately understandable patterns in data and converting it into useful information [3]. An overview of the steps constituting the KDD process is depicted in Figure 1.1.

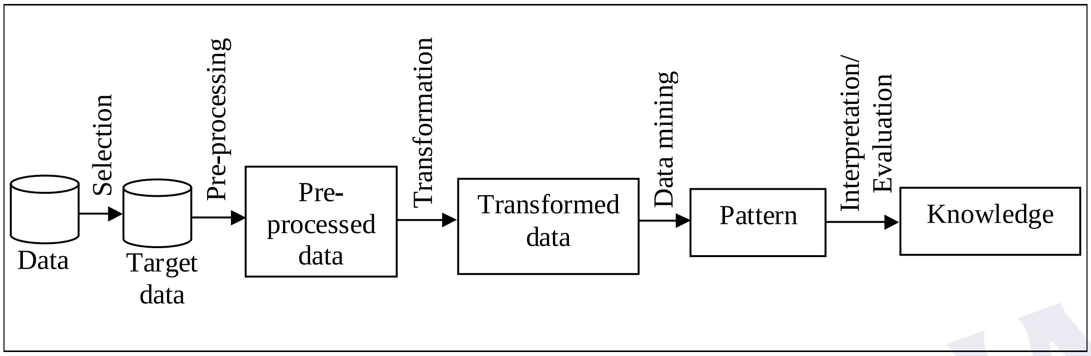

Figure 1.1. The processes of KDD [3]

Data mining in KDD applies a specific algorithm to extract meaningful knowledge so that the discovered knowledge can be applied in the related area to increase working efficiency and also to improve the quality of decision-making. Data mining involves several steps such as data integration from various databases, data pre-processing, and induction of a model using a learning algorithm. Based on the requirements of the problem domain, various techniques that expose diverse kinds of patterns from a given dataset have been implemented in data mining. The most common techniques learned in data mining include data classification, data clustering, association rule discovery, and outlier detection.

1.2. Motivation and Problem Statements

As mentioned earlier, data mining has been widely used to solve various kinds of data classification problems. However, data classification has turned out to be one of the most pervasive problems that encompasses many diverse applications in the data mining field. These problems have attracted more active research in order to find efficient approaches to address them, and the outcome of the research is still unsatisfactory.

The ultimate goal of classification is to discriminate new data into the most likely of the specific categorical variable (the class) based on the induction model generated by the classifier. However, the classification problem has become very complicated and computationally infeasible when the number of possible different combinations of variables is so high. Hence, Swarm Intelligence (SI) algorithms are generally more suitable to solve these difficult problems because they are based on stochastic population-based approaches. In addition, they are also capable of avoiding becoming stuck in a local optimal and can find a global optimal solution [4].

Many data mining approaches have been proposed using stochastic population-based algorithms such as Particle Swarm Optimization (PSO), Immune Algorithm (IA), Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO). Nevertheless, there are problems in real-world that are NP-hard and combinatorial. Thus, evolutionary algorithm like PSO is generally more suitable to solve these difficult problems because of its stochastic nature. PSO is a well-known, biologically inspired computational search and optimization algorithm which is based on the social behaviours of bird flocks or schools of fish [5]. Because of its easy implementation, PSO has been successfully applied in many fields, particularly in optimization applications [6] and data mining [6-8]. This is due to its simplicity and efficiency when navigating a search space for optimal solutions. In terms of data mining, PSO has emerged as a promising technique to discover useful and interesting knowledge from databases [8]. Because of these advantages, the motivation of this thesis is to develop a new data mining technique based on the original PSO algorithm.

In many applications, people are dealing with massive data that contains multi-dimensional attributes such as network intrusion data, stock market data, medical data, weather forecast data and much more. Thus, data classification is faced with a problem when it has to generate rules with many attributes or features. Obviously, the time required to generate rules is proportional to the number of features. In addition, irrelevant and redundant features can reduce both the predictive accuracy and comprehensibility of the induced rule and degrade the classifier speed (due to its high dimensionality). Thus, selecting the most relevant features is necessary, and this strategy is implemented to simplify the rules and reduce its computational time while retaining the quality of classification, as it represents the original features set.

This thesis proposes and investigates the application of a new efficient population-based optimization algorithm for data mining based on the PSO algorithm. The new technique is referred as a Simplified Swarm Optimization (SSO) algorithm. Like PSO, SSO solves data mining problems by simulating the social interaction among agents or particles in their population, such as birds flocking or fish schooling. To deal with the problem of feature selection, a new hybrid swarm intelligence-based rough set theory for feature selection using SSO is proposed as a way to improve some performance criterion, such as accuracy of data classification. In this thesis, the author is concerned with introducing a new population-based optimization technique for data mining and feature selection that contributes to maximising the classification accuracy. Therefore, computation time is not taken into consideration.

Throughout this thesis, each algorithm was implemented using Java NetBeans IDE 6.1 on the following system: 1.8GHz Pentium (R) processor and 2GB RAM running in Windows XP Professional. Five traditional classifiers were involved in the experiments for comparison with the proposed technique. Those benchmark classifiers were implemented from Waikato Environment for Knowledge Analysis (WEKA) [1]. The employed classifiers were set with their default parameters as set in WEKA.

1.3. Objectives and Contributions of the Thesis

This section outlines the main objectives and contributions to the area of data mining, particularly in feature selection and classification problems.

i. To develop and implement an efficient data classification technique based on an SSO algorithm to be implemented in audio datasets.
ii. To develop and implement a novel Exchange Local Search (ELS) strategy to improve the performance of the SSO rule-based classifier on various datasets.
iii. To develop and implement a new hybrid SSO-based Rough Set for feature selection and Weighted Local Search (WLS) strategy with SSO classifier to improve the Anomaly-based Network Intrusion Detection System (A-NIDS).

1.4. Outline of the Thesis

The remainder of this thesis is structured as follows:

"CHAPTER 2 Literature Review of Feature Selection and Data Mining" comprehensively presents two main topics that cover the foundations of feature selection and data mining. These topics provide a review of recent work that has been conducted in feature selection (with more emphasis on Rough set theory) and in data mining (with more emphasis on traditional classification techniques).

“CHAPTER 3 Data Mining using the Particle Swarm Optimization Algorithm” provides some introduction to four population-based optimization algorithms (with more emphasis on the PSO). This chapter also reviews the implementation of PSO algorithms for data mining purposes in various applications and problem domains. Four approaches have been highlighted in PSO-based classification including: PSO for Rule-based Classification Model, Nearest Neighbor Classification, PSO as Optimizer within Other Learning Algorithms, and Clustering with PSO Algorithms. Also, some PSO variants for data classification are discussed in this chapter.

“CHAPTER 4 Data Mining using Simplified Swarm Optimization Algorithm” presents the Simplified Swarm Optimization (SSO) algorithm that is based on traditional PSO for data mining. This is followed by the principle of the SSO algorithm; the SSO rule mining scheme; the SSO rule evaluation; and SSO rule pruning. The proposed algorithm is then applied to audio data and it is compared with Support Vector Machine (SVM) to investigate its competitiveness.

“CHAPTER 5 The Proposed SSO with Exchange Local Search for Data Classification” presents a proposed Exchange Local Search (ELS) strategy to be incorporated with SSO for data classification. To show the applicability of the proposed approach, SSO with ELS (SSO-ELS) is then applied to 13 datasets obtained from public sources such as the UCI repository database. The performance is compared with and without ELS for SSO and PSO, and four other traditional classifiers including SVM, J48, PART and kNearest Neighbor.

“CHAPTER 6 A Hybrid SSO-based Rough Set Reduction Method for Network Intrusion Detection Systems” introduces a proposed hybrid SSO-based rough set reduction for features dimensionality reduction. This approach is specifically applied to solve the classification problem in Anomaly-based Network Intrusion Detection Systems (A-NIDS) due to its large amount of attributes. This is followed by the principle of the proposed SSO with Weighted Local Search (WLS) strategy for mining anomaly intrusion patterns. The experimental results, when compared with original SSO and PSO, and also with SVM and Naive Bayes, show the effectiveness of hybridizing SSO-WLS approaches for A-NIDS detection.

“CHAPTER 7 Conclusions and Future Work” contains a summary, conclusion, limitations and future direction of the research conducted in this thesis.

CHAPTER 2. Literature Review of Feature Selection and Data Mining

In recent years, the field of automated data mining has emerged as an important area of applied research when dealing with the voluminous data collected in various industries. This is due to the low cost and availability of larger storage devices. Thus, two major data mining tasks that must be solved are feature selection and classification. In this chapter, the investigation on several techniques of feature selection and data classification is continued, and comprehensive reviews on both topics are presented in section 2.1 and section 2.2. In this thesis, the new data mining algorithms based on the population-based optimization algorithm are proposed in Chapter 3.

2.1. Feature Selection Overview

Feature selection plays an important role in data pre-processing technique for data mining [2]. It is a process of finding a subset of features from the original set of features, and forming patterns in a given dataset to obtain the optimal one according to the given goal of processing and criterion. It reduces the number of features, removes irrelevant, redundant, or noisy data and brings immediate effects for applications: speeding up a data mining algorithm, improving mining performance such as classification accuracy, and improving results comprehensively.

In the context of classification, feature selection can be structured into three fractions: *filter* method, *wrapper* method and *embedded* method [9]. Filter methods rely on the intrinsic properties of the training data to select some features without involving any learning algorithm. Each feature is ranked according to some univariate metric, and only the highest ranking features are used while the remaining low ranking features are eliminated. Afterwards, this subset of features is presented as input to the classification algorithm. Therefore, feature selection is allowed to be performed only once, and then different classifiers can be evaluated. A number of multivariate filter techniques were introduced to overcome univariate problems in filter methods.

Wrapper methods embed the model hypothesis search within the feature subset space. These methods begin by looking for the dependency from a suboptimal subset. Then this value is fed into the fitness function of the selected learning algorithm and evaluated in order to find the suitable features. These methods suffer from a high risk of overfitting and require huge computational cost.

Meanwhile, in the third category of feature selection, namely, embedded methods, the search for an optimal subset of features is built into the classifier construction, which can be seen as a search in the combined space of feature subsets and hypotheses. Thus, their function is seen as more specific to a given learning algorithm. Embedded methods are less computationally intensive than wrapper methods due to the internal interaction with the classification model during the feature selection process.

2.1.1. Feature Selection Problems

The feature selection problem is more or less a special case of a much broader problem of subset selection. Suppose a large set of M items $\{x_k,y_k\}$ where $k = 1, 2,\ldots,$ M consisting of n input variables $x_{k,i}$ where $i = 1, 2,\ldots, n$ and one output variable y_k is given from which we need to find a small m subset being optimal in a certain sense. Fitness function (F_i) is computed from the values $x_{k,i}$ and y_k , $k = 1, 2,\ldots, m$ to rank the

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